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Frederic M. Lord

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If a loss function is available specifying the social cost of an error of measurement in the score on a unidimensional test, an asymptotic method, based on item response theory, is developed for optimal test design for a specified target population of examinees. Since in the real world such loss functions are not available, it is more useful to reverse this process; thus a method is developed for finding the loss function for which a given test is an optimally designed test for the target population. An illustrative application is presented for one operational test.

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Abstract

If a loss function is available specifying the social cost of an error of measurement in the score on a unidimensional test, an asymptotic method, based on item response theory, is developed for optimal test design for a specified target population of examinees. Since in the real world such loss functions are not available, it is more useful to reverse this process; thus a method is developed for finding the loss function for which a given test is an optimally designed test for the target population. An illustrative application is presented for one operational test.

Estimating the Imputed Social Cost of E ... nt*

For a unidimensional test, the error of ... trement ... t dif-ference between the examinee's true ability ... and the estimate of this ability represented by the examinee's test ... discrepancies between $\hat{\theta}$ and θ may lead to erroneous ... the examinee (misclassification, erroneous acceptance o ... on, there is an expected social cost associated with any p ... es, $(\hat{\theta},\theta)$. This cost is given by some loss function $L(\hat{\theta},\theta)$.

The obvious problem, here called Problem 1, is: Given the loss function $L(\hat{\theta},\theta)$, how can we build an (optimal) n-item test that will minimize the expected loss over a specified target population of examinees, subject to certain constraints on the statistical characteristics of the items in the available item pool? Using item response theory, [Lord, 1980; Hulin, Drasgow, and Parsons, 1983], a solution of this problem will be given here for a unidimensional test.

Unfortunately, in practice, it is unlikely that $L(\hat{\theta},\theta)$ will be known to the test designer. Something of practical value can still be salvaged, however, if we can deal with Problem 2: Given an existing unidimensional test and a specified target population of examinees, find the loss function $L(\hat{\theta},\theta)$ for which this test is an optimally designed test. If the

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loss function found for Problem 2 does not agree with our intuitive notions as to what is appropriate, we will probably redesign future test forms to avoid this discrepancy.

In order to solve Problem 2, it is necessary first to solve Problem 1; this is done in the first section. The solution to Problem 2 is outlined in the second section. Invariance under transformations of the ability scale is discussed in Section 3. In Section 4, a method for estimating the ability distribution of the target population is discussed. An illustrative application to an actual test is given in Section 5. The final section briefly discusses some implications for optimal test design.

It is assumed here that all item parameters have been determined by pretesting to sufficient accuracy so that they can be treated as known. The illustrative example and some of the discussion are based on the three-parameter logistic model of the item response function (with which the reader is assumed to be familiar), but the proofs of the main results are much more general. The examinee's actual score $\hat{\theta}$ is assumed to be the maximum likelihood estimate of θ, calculated from the examinee's responses to the n test items.

1. Minimizing Expected Loss

For a group of examinees at a given ability level θ, the conditional expected loss is by definition

$$\mathcal{E}(L|\theta) = \int_{-\infty}^{\infty} L(\hat{\theta},\theta)\,\phi(\hat{\theta}|\theta)\,d\hat{\theta} \qquad (1)$$

where $\phi(\hat{\theta}|\theta)$ is the conditional distribution of $\hat{\theta}$ and $\mathcal{E}$ denotes expectation. If the distribution of ability θ in the target population is denoted by $g(\theta)$, then the overall (unconditional) expected loss is by definition

$$\mathcal{E}(L) = \int_{-\infty}^{\infty} \mathcal{E}(L|\theta)\,g(\theta)\,d\theta \qquad (2)$$

This is the quantity to be minimized by optimal test design.

Loss Function

Certain reasonable assumptions will be made about the loss function:

1. $L(\theta,\theta) = 0$ (because when $\hat{\theta} = \theta$, there is no error of measurement and hence no loss due to error of measurement).
2. When $\hat{\theta} \neq \theta$, $L(\hat{\theta},\theta) > 0$.
3. When $\hat{\theta}$ is near θ, the loss function and its first two derivatives with respect to $\hat{\theta}$ are continuous, the third derivative is bounded. [These conditions will guarantee the convergence of (3).]
4. The loss function does not change too sharply with changes in θ (as will be discussed later).

For fixed θ, expand $L(\hat{\theta},\theta)$ in powers of $\hat{\theta} - \theta$, obtaining

$$L(\hat{\theta},\theta) = L(\theta,\theta) + (\hat{\theta} - \theta)L'(\theta,\theta) + \frac{1}{2}(\hat{\theta} - \theta)^2 L''(\theta,\theta) + \ldots$$

where $L'(\theta,\theta)$ and $L''(\theta,\theta)$ denote successive derivatives of $L(\hat{\theta},\theta)$ with respect to $\hat{\theta}$, evaluated at $\hat{\theta} = \theta$. The first term vanishes because there is no error of measurement when $\hat{\theta} = \theta$. The second term vanishes because for fixed θ, $L(\hat{\theta},\theta)$ has a minimum at $\hat{\theta} = \theta$. Consequently,

$$L(\hat{\theta},\theta) = \frac{1}{2}(\hat{\theta} - \theta)^2 L''(\theta,\theta) \text{ plus higher order terms.} \tag{3}$$

Higher powers of $(\hat{\theta} - \theta)$ can be neglected if n is not too small, since $\hat{\theta} \to \theta$ in probability as $n \to \infty$ [Lord, 1980, p. 59].

When (3) is substituted into (1), $L''(\theta,\theta)$ comes out from under the integration sign. It is then apparent that asymptotically (that is, for large n)

$$\mathcal{E}(L \mid \theta) = \frac{1}{2} L''(\theta,\theta) \operatorname{Var}(\hat{\theta}\mid\theta) . \tag{4}$$

In item response theory, the asymptotic (conditional) variance of $\hat{\theta}$ is the reciprocal of the test information function $I(\theta)$ [Lord, 1980, Section 5.3]. Thus we shall rewrite the expected loss (2) as

$$\mathcal{E}(L) = \frac{1}{2} \int_{-\infty}^{\infty} \frac{L''(\theta,\theta)\, g(\theta)}{I(\theta)} d\theta . \tag{5}$$

Information Function

The item response function $P_i \equiv P_i(\theta)$ is the probability of a correct response to item i by a randomly chosen examinee at ability level θ. The information function is

$$I(\theta) = \frac{1}{\mathrm{Var}(\hat{\theta}|\theta)} = \sum_{i=1}^{n} \frac{P_i'^2}{P_i Q_i} \tag{6}$$

where $Q_i \equiv 1 - P_i$ and $P_i' \equiv dP_i/d\theta$.

Ordinarily, P_i depends on an item difficulty parameter b_i. Furthermore, b_i is typically simply a translation parameter: it affects P_i only through the difference $\theta - b_i$. In this standard situation, b_i also affects P_i' only through the difference $\theta - b_i$. Thus the area under any function F of P_i and P_i' over the whole range of θ

$$\int_{-\infty}^{\infty} F(\theta - b_i)\, d\theta = \int_{-\infty}^{\infty} F(\theta)\, d\theta$$

is independent of b_i. The area under the test information function thus does not depend on b_i in these typical models, which will be assumed here.

In the special case where $P_i(\theta)$ is the three-parameter logistic function,

$$P_i(\theta) = c_i + \frac{1 - c_i}{1 + \exp[-1.7a_i(\theta - b_i)]} \tag{7}$$

we have

$$P_i' = \frac{1.7a_i}{1 - c_i} Q_i (P_i - c_i)$$

and

$$\int_{-\infty}^{\infty} I(\theta)\, d\theta = \int_{-\infty}^{\infty} \sum_i \frac{P_i'^2}{P_i Q_i} d\theta \equiv \sum_i \int_{-\infty}^{\infty} \frac{P_i'}{P_i Q_i} \frac{dP_i}{d\theta} d\theta = \sum_i \int_{c_i}^{1} \frac{P_i'}{P_i Q_i} dP_i$$

$$= \sum_i \frac{1.7a_i}{1 - c_i} \int_{c_i}^{1} (1 - \frac{c_i}{P_i}) dP_i = \sum_i \frac{1.7a_i}{1 - c_i} [P_i - c_i \log P_i]_{c_i}^{1}$$

$$= \sum_{i=1}^{n} \frac{1.7a_i}{1 - c_i} (1 - c_i + c_i \log c_i) \quad (8)$$

This area does not depend on b_i.

Test Constraints

There are always constraints on the availability of items for test construction. Item writers can control to a considerable extent the difficulty level of the items they write. The discriminating power of the available items, however, can ordinarily be increased only by writing more items and then discarding a larger percentage of the items written--an expensive procedure.

It will be assumed here that the test developer has available an unlimited pool of items at whatever difficulty levels he or she may specify. The items in the pool have already been pretested; faulty items, especially those with low discriminating power, have already been discarded. The test developer is to build parallel forms of a test from the item pool, selecting items only on the basis of their difficulty b_i.

so that each parallel form has the same distribution of b_i. Items cannot be selected on the basis of their discriminating power, since all items not discarded after pretesting must eventually be used. In the actual test produced, the frequency distribution of other item parameters, such as item discriminating power, is to be the same as in the total pool of pretested items. It will be assumed here that in the item pool the distribution of other item parameters is independent of the item difficulty b_i. This assumption should be checked empirically for any practical application.

This assumption may fail to hold because of the essential nature of the test items; often it also fails to hold simply because pretest item-test biserials have been used instead of the IRT discrimination parameter a_i to exclude poorly discriminating items from the available item pool. When item-test biserials are used in this way for multiple-choice items, the harder the item, the higher the a_i parameter must be for the item to escape exclusion from the item pool. This is true because among items with identical a_i, the more guessing the lower the item-test biserial.

It follows from these assumptions that the total area under the test information function is fixed. The task of the test developer is to minimize $\mathcal{E}(L)$ by choice of b_i ($i = 1,2,\ldots,n$); no other relevant variables are available to the test developer for achieving this minimization.

Minimization

By the Cauchy inequality,

$$\int \frac{L''g}{I} \cdot \int I \geq \left(\int \sqrt{L''g} \right)^2 .$$

Here, the first integral is twice the expected loss (5) written in abbreviated notation. Transposing, we have

$$\int \frac{L''g}{I} \geq (\int \sqrt{L''g})^2 \div \int I \quad . \tag{9}$$

In Problem 1, $L''(\theta,\theta)$ and $g(\theta)$ are known; furthermore $\int_{-\infty}^{\infty} I(\theta)\,d\theta$ is fixed by the reasoning of the last two subsections. It follows that if there is an $I(\theta)$ such that equality holds in (9), then this is the $I(\theta)$ that minimizes the expected loss (5). Equality will hold in (9) provided

$I(\theta)$ is proportional to $\sqrt{L''(\theta,\theta)\ g(\theta)}$.

Monetary Units

The loss function $L(\hat{\theta},\theta)$ is necessarily expressed in terms of some arbitrary unit (dollar, peso, ...). It may be convenient to choose this unit so that the area under $\sqrt{[L''(\theta,\theta)\ g(\theta)]}$ is equal to $\int_{-\infty}^{\infty} I(\theta)\,d\theta$, this last being a known and fixed quantity determined by n and by the item parameters, excluding the b_i , of the item pool. Once this choice of unit has been made, the expected loss will be minimized if the test developer can build a test with

$$I(\theta) = \sqrt{L''(\theta,\theta)\ g(\theta)} \quad . \tag{10}$$

Building the Test

Birnbaum [1968, Section 20.6] suggested an effective cut-and-try method for building a test having (approximately) a prespecified 'target' information function. The method is outlined in Lord [1980, Section 5.4]. The method follows easily from the fact that the test information function is simply a sum of the information functions $(P_i'^2/P_iQ_i)$ of the items included in the test.

The method is effective provided the target information curve is not too irregular and does not vary too rapidly as a function of θ. The results obtained here hold under this condition. If the target curve is too irregular, it will not be possible to build a test having the desired information function by selecting items on b_i from the available item pool.

Practical Procedure (Summary)

Given $L(\hat{\theta},\theta)$ and $g(\theta)$, to build k parallel test forms of length n that approximately minimize the expected loss:

1. Plot a_i and c_i against b_i to verify that the distribution of a_i and c_i in the item pool is approximately the same at all levels of b_i, as assumed in the subsection titled Test Constraints.

2. Compute

$$\int_{-\infty}^{\infty} I(\theta)\, d\theta = \frac{n}{M} \sum_{i=1}^{M} \int_{-\infty}^{\infty} \frac{P_i'^2}{P_iQ_i}\, d\theta$$

where M is the number of items in a large item pool. Note that this integral does not depend on the distribution of b_i in the pool.

3. Choose monetary units so that

$$\int_{-\infty}^{\infty} \sqrt{[L''(\theta,\theta)\ g(\theta)]}\ d\theta$$

is equal to

$$k \int_{-\infty}^{\infty} I(\theta)\ d\theta$$

for some integer k .

4. Selecting items only on their b_i , use Birnbaum's method to select a pool of nk items such that the sum of the nk item information functions is approximately equal to $\sqrt{[L''(\theta,\theta)\ g(\theta)]}$.

5. Divide the nk selected items into k test forms of n items each, all approximately parallel to each other.

2. The Loss Function for Which a Given Test Is an Optimal Test

If a given test is an optimal test, then (10) holds and

$$L''(\theta,\theta) = \frac{I^2(\theta)}{g(\theta)} \qquad (11)$$

Consequently, the loss function is given approximately by (3) and (11):

$$L(\hat{\theta},\theta) = \frac{1}{2}\,\frac{I^2(\theta)}{g(\theta)}\,(\hat{\theta} - \theta)^2 \qquad (12)$$

For fixed θ, this is the equation of a parabola. When n is not too small, $\hat{\theta}$ will be close to θ and (12) will provide an adequate approximation to the loss function for those values of θ that are likely to be observed. For $\hat{\theta}$ close to θ, the desired loss function can be computed from (12) for any given test, provided $g(\theta)$ is specified.

3. Transformation of the Score Scale

Loss functions have an invariance property that is important in dealing with problems of test design. Consider the social cost in dollars of an error of measurement at a given ability level. If the error of measurement (the discrepancy between the actual test score and the true ability of which it is an estimate) is specified as a multiple of its standard error, asymptotically (for large n) the loss in dollars will be the same no matter what scale is used for measuring ability.

Instead of using the θ scale of ability, suppose we use the number-right true-score scale, given by the monotonic continuous transformation

$$\xi = \sum_{i=1}^{n} P_i(\theta) \tag{13}$$

The examinee's obtained score should now be taken to be

$$\hat{\xi} = \sum_{i=1}^{n} P_i(\hat{\theta}) \tag{14}$$

(Note that we need to use here the maximum likelihood estimator of ξ defined by (14), not the examinee's number of right answers.) If $\hat{\theta}$ differs from θ by K times $S.E.(\hat{\theta}|\theta)$, then, asymptotically, $\hat{\xi}$ will differ from ξ by K times $S.E.(\hat{\xi}|\xi)$. Asymptotically, $K[S.E.(\hat{\theta}|\theta)]$ is actually the same error of measurement on the θ scale as $K[S.E.(\hat{\xi}|\xi)]$ is on the ξ scale; thus the social consequences of this error will be the same regardless of the scale used.

Let $\theta(\xi)$ denote the inverse of transformation (13). Expressed on the ξ scale, the loss function (12) becomes

$$L_{\xi}(\hat{\xi},\xi) = \frac{1}{2}\,\frac{I^2[\theta(\xi)]}{g[\theta(\xi)]}\,[\theta(\hat{\xi}) - \theta(\xi)]^2$$

where $g(\ )$ and $I(\ )$ denote the same functions as previously. This equation could be used as it stands, but for reasons of symmetry, it may be preferable to expand it for fixed ξ in powers of $\hat{\xi} - \xi$. The result is found to be

$$L_{\xi}(\hat{\xi},\xi) = \frac{1}{2}\,\frac{I^2[\theta(\xi)]}{g[\theta(\xi)]}\,\left[\frac{d\theta(\xi)}{d\xi}\right]^2 (\hat{\xi} - \xi)^2 \ . \qquad (15)$$

Equation (15) is used here to represent the loss function when the obtained score is $\hat{\xi}$ rather than $\hat{\theta}$. This transformation has an advantage for presenting experimental results, since the number-right score scale is more familiar to us than the θ scale.

Note again that the actual monetary loss is the same regardless of the scale against which it is plotted. This invariance makes the loss function much more useful for guiding test design than the information function. Expressed on the θ scale, the test information function for θ is typically a bell-shaped curve; expressed on the ξ scale, the test information function for ξ is necessarily a U-shaped curve [Lord, 1980, Chapter 6]. This lack of invariance makes it difficult to use the test information function as a convincing basis for test design.

4. Estimating the True $g(\theta)$

By its definition, expected loss (2) requires specification of the distribution θ in the target population. It is important to note that the distribution of $\hat{\theta}$ in the target population is not an adequare estimate of $g(\theta)$, the true distribution of θ. The reason is that $\hat{\theta}$ contains errors of measurement and thus has a larger variance than θ. Since $g(\theta)$ appears in the denominator of (12), it is particularly important to estimate $g(\theta)$ as accurately as possible.

To obtain the numerical results of Section 5, the true distribution of number-right true score (13), here denoted by $f(\xi)$, was estimated by Method 20 [Lord, 1980, Chapter 16]. Since ξ is necessarily $\geq \Sigma_i P_i(-\infty)$, an estimated lower limit for ξ was set at $\Sigma_i \hat{c}_i$, where $\hat{c}_i$ represents the estimated c parameter of item i. For purposes of Section 5 all item parameters were estimated under the three-parameter logistic model (7) by the computer program LOGIST [Note 1].

The required estimate of $g(\theta)$ for the target population was obtained from the Method 20 estimate of $f(\xi)$ by the relation

$$g(\theta) = f(\xi)\frac{d\xi}{d\theta} . \tag{16}$$

The derivative in (16) is the derivative of (13), estimated in practice by computing $\Sigma_i P_i'(\theta)$ from estimated item parameters.

5. Illustrative Example

A representative sample of 19,949 examinees tested in 1981-82 was obtained for the Sentence Sense test in Form 3EJP of the New Jersey College Basic Skills Placement Test. This competency test consists of 35 four-choice items requiring the examinee to distinguish correct from incorrect English expression. The test is used primarily to assign certain entering college students to remedial English classes.

The item responses of all 19,949 examinees were analyzed, using LOGIST to estimate the item parameters of all items in the test. The true distribution of θ for the target population was estimated as described in Section 4 (for this purpose, a response chosen at random from the four choices was supplied wherever an examinee failed to respond to an item). The test information function (6) was calculated from the estimated item parameters. Finally, the loss function for which the test is an optimally designed test was estimated by (12).

Figure 1 shows the actual distribution of number-right scores (frequency polygon), the number-right true-score distribution estimated by Method 20 (solid curve), and the corresponding fitted distribution of (observed) number-right scores (dotted curve). The modal score is 31 right answers out of a possible 35. The chi square between observed and fitted number-right score distributions is at the 86th percentile of the chi square distribution with 18 degrees of freedom. In view of the large sample size ($N = 19{,}949$), this seems an adequate fit, as in indeed suggested visually by the agreement shown in Figure 1.

The estimated loss function (12) for which the test is an optimally designed test is plotted in Figure 2 against the θ and $\hat{\theta}$ Scales. The direction of the $\hat{\theta}$ scale is reversed from the conventional direction in order to improve visibility. Loss is shown on the vertical scale. In this and the next figure, the parabola for any given θ is drawn only for $\hat{\theta}$ values within two standard errors of the true θ .

The figure shows that the Sentence Sense test is built as if it were important to measure accurately at high ability levels as well as at low ability levels. Clearly, this is not appropriate for a competency test--the test should assign high losses to errors of measurement at low ability levels but <u>not</u> at high ability levels. The more difficult items in the test should be replaced by easier items.

The estimated loss function (15) for which the test is an optimally designed test is plotted in Figure 3 against number-right true score and

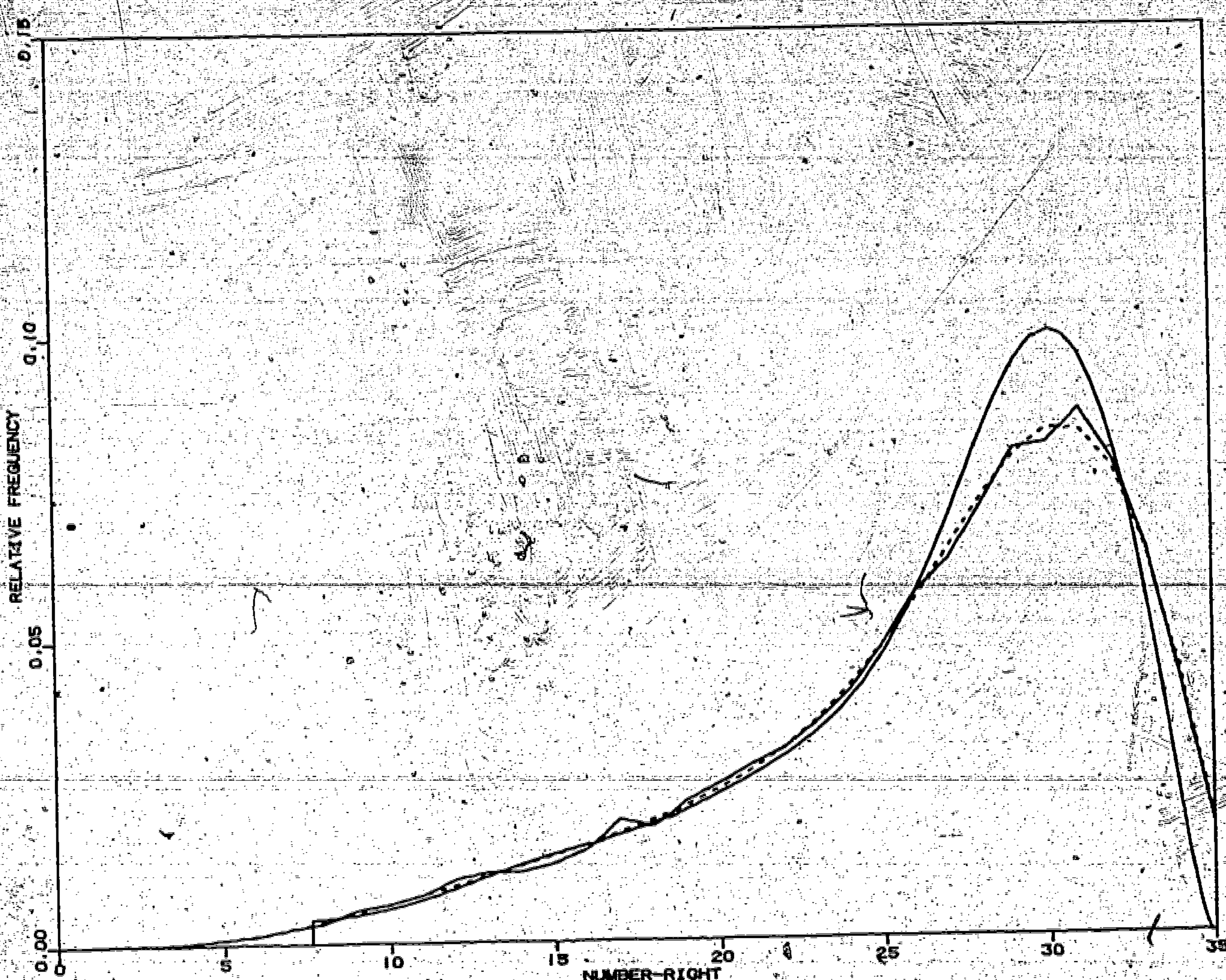

Figure 1. Frequncy distributions of true and observed number-right scores for NJCBSPT Sentence Sense, Form 3EJP, N = 19949 .

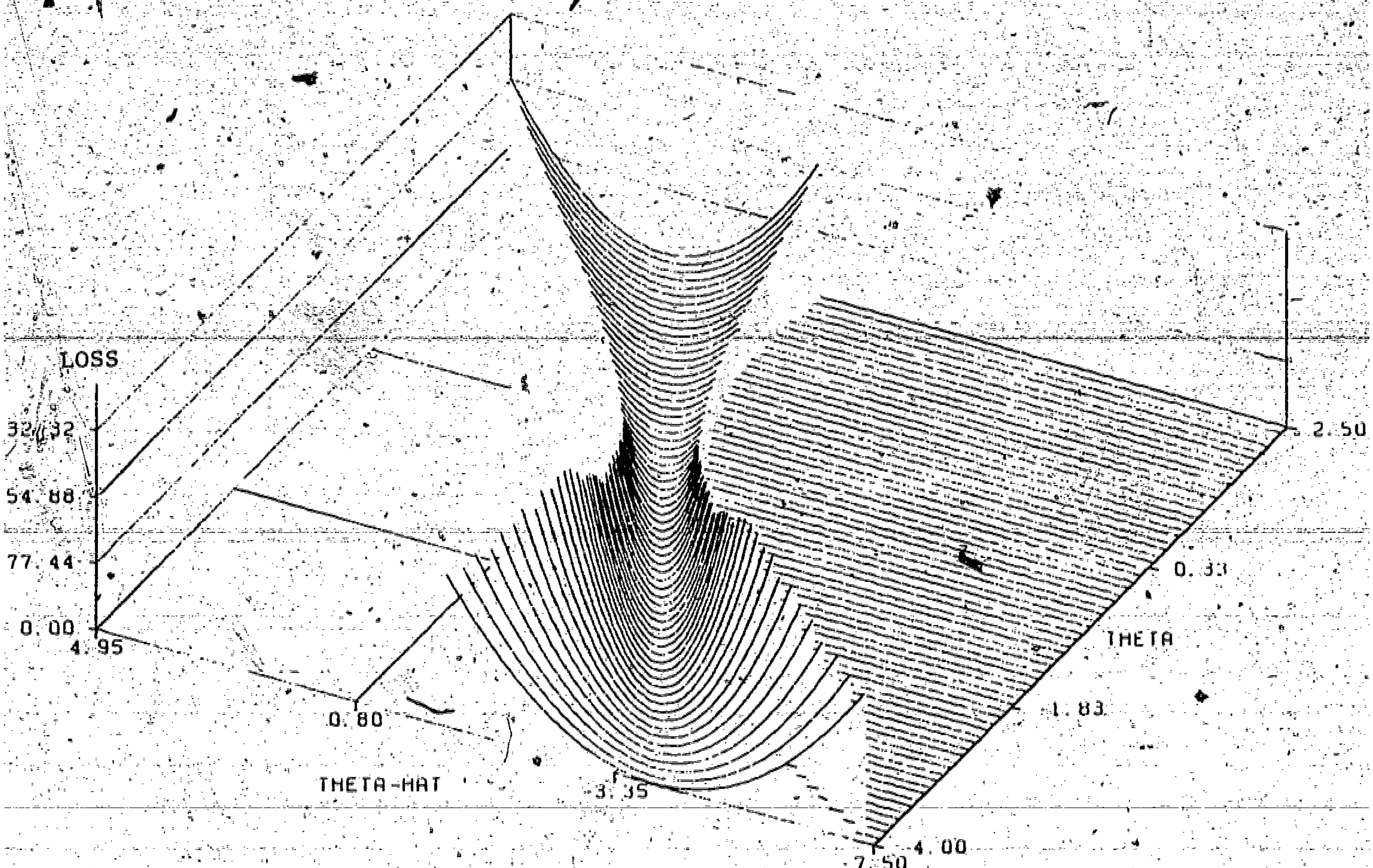

Figure 2. Loss function for NJBSCPT, 3EJP, Sentence Sense, N = 19949 .

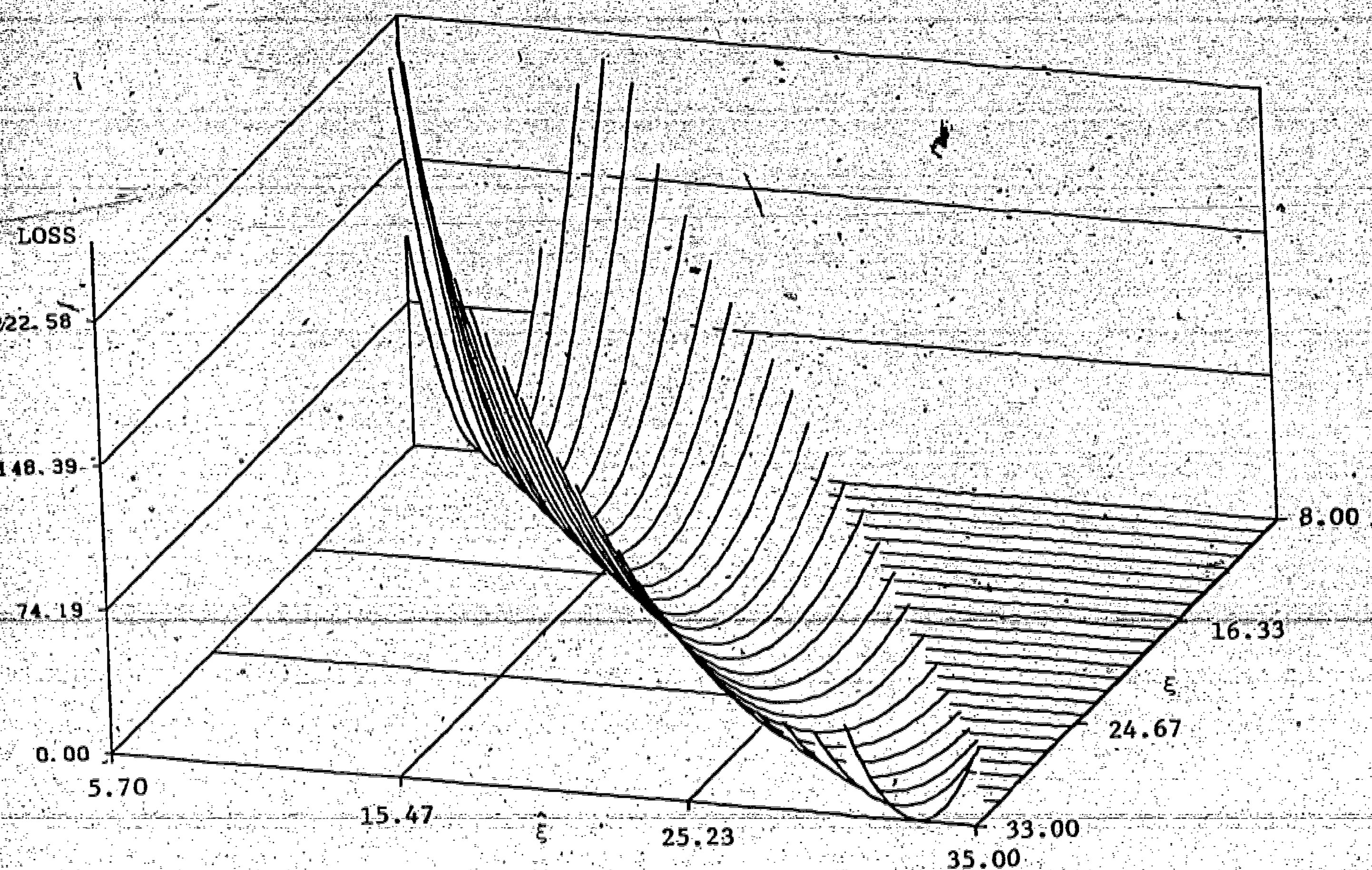

Figure 3. Estimated Loss Function for NJBSCPT, 3EJP, Sentence Sense, N = 19949, as a function of true score (ξ) and estimated true score ($\hat{\xi}$).

estimated number-right true score. For ease of viewing, both scales at the bottom of the figure run in the opposite direction from the scales at the bottom of Figure 2. This plot is easier to interpret than Figure 2 since we are more accustomed to the number-right score scale than to the θ scale. The plot looks very different from Figure 2 because

1. The loss function for a number-right score of 34 is not shown. The loss function for this score is rather high and would obscure too much of the rest of the figure.
2. A wide range at the high end of the θ scale is compressed into a small range of number-right scores, as shown in the following table:

ξ :	8	10	12	14	16	18	20	22	24	26	28	30	32	34
θ :	-5.2	-3.1	-2.4	-1.9	-1.6	-1.3	-1.0	-.7	-.4	-.2	.1	.5	1.0	2.1

Again, it appears that the test discriminates at high true score levels, where discrimination is not really desired. The loss function at $\xi = 34$ (not plotted) shows a loss of approximately 100 when $\hat{\xi}$ is two standard errors from ξ. For number-right scores of 30 and below, the shape of the loss function seems very appropriate for a competency test, with very high losses attributed to errors of measurement at low score levels.

6. Discussion

In the case of a minimum competency test, the social losses arising from errors of measurement will be high for examinees near the cutting score, which is always near the low end of the score scale. Social losses will be near zero for examinees far from the cutting score, since decisions about these examinees will not be changed by small errors in their scores.

For a college admissions test, it would seem reasonable to expect that errors of measurement in the scores of high ability sutdents will result in relatively high social losses. Somewhat lower social losses should be expected to result from errors in the scores of low ability students.

In the case of grade school tests of 'ability' or of vocabulary, it has sometimes been argued that, to be fair, the standard error of measurement of the test score should be roughly the same for each individual (see, for example, Hulin et al., 1983, p. 90). The first difficulty with this approach is that its implications for test design when the test score is $\hat{\theta}$ are completely different than when the test score is $\hat{\xi}$ or simply the number of right answers. Although equality of standard errors of measurement at all ability levels has strong intuitive appeal, there is no clear way to decide whether this equality should hold on the θ scale, or on the number-right score scale, or on some other scale. It cannot hold simultaneously on two different scales unless one scale is a linear transformation of the other.

In any case, any goal of equal standard errors of measurement at different ability levels is completely incompatible with the goal of minimizing expected social loss due to errors of measurement. If we wish to minimize social loss, we must, other things being equal, mobilize our test development resources so as to measure most accurately at those ability levels where the most people are found. We cannot waste items in order to secure accurate measurement at ability levels where only a few people will be affected, unless, of course, there is a very high loss function at these ability levels. In a word, accuracy of measurement in sparsely populated stretches of the ability range must be sacrificed, other things being equal, in order to obtain more accurate measurement in heavily populated stretches.

As a concrete example, consider a vocabulary test for grade 5 and suppose our test is built to minimize overall expected loss. Suppose also, as might be reasonable for such a test, that the expected loss at a fixed ability level is constant across ability levels, so that, by (12),

$$\mathcal{E}[L(\hat{\theta},\theta)|\theta] = \frac{1}{2}\,\frac{I^2(\theta)}{g(\theta)}\,\mathcal{E}[(\hat{\theta}-\theta)^2|\theta] = \frac{1}{2}\,\frac{I^2(\theta)}{g(\theta)}\,\frac{1}{I(\theta)} = K$$

where K is some constant. It follows that

$$\mathrm{Var}(\hat{\theta}|\theta) = \frac{1}{I(\theta)} = \frac{1}{2Kg(\theta)}$$

Since $g(\theta)$ is small for extreme θ, the standard error of measurement, $\sqrt{Var(\hat{\theta}|\theta)}$, will in this case be very much larger for examinees with extreme θ than for examinees with moderate θ. Thus in this case the goal of equal standard errors of measurement at all ability levels is utterly incompatible with minimizing overall expected loss. This is simply an illustration of the fact that if we wish to minimize overall expected loss, our measurement effort must be concentrated on the subranges of ability that are most highly populated in the target population.

To summarize, in respect to a unidimensional test:

1. Given the loss function, the distribution of ability in a target population, and certain constraints on the available item pool, a method has been described for designing a test that will minimize expected loss.

2. Given a test and also the distribution of ability in the target population, a method has been described for finding the loss function for which this test is an optimally designed test given certain constraints on the available item pool.

3. Minimizing social loss is in general incompatible with equal measurement accuracy across examinees. To minimize social loss, measurement accuracy must be high (other things being equal) over ability ranges that are heavily populated, and relatively low over ranges that are sparsely populated.

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